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Condition-Based Maintenance of Pumps: Evaluating the Effectiveness of Parameter Indicators

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ABSTRACT

Maintenance of pumps is a routine activity carried out in all flow stations in the oil and gas industry, hence, there is a growing concern to optimize its operation to reduce downtime and maximize productivity. To this end, this study aimed at evaluating the effectiveness of parameter indices as indicators in Condition Based Monitoring (CBM) of centrifugal pump bearing. Leading/output indicators that interface with the maintenance schedule and procedure were evaluated. These indicators establish the current state of the plant and identify what parameters/activity is responsible for a noted trend. The relationship between the pump maintenance procedure and the state of the centrifugal pump was established using vibration analysis. This was achieved by using the Fast Fourier Transform (FFT) technique and validated using the Genetic Algorithm (GA) method. The result of the study shows that at the current operating condition of the flow station, failure in the pump is expected after 9480 hours of operation, and this failure is due to subsurface fatigue, and coupling damage. A model and chart were developed which is instructive in scheduling maintenance operations to avoid an unnecessary halt in the production line due to the failure of a component. The study concludes that the use of parameter indicators is a necessary guide in positioning a production line/manufacturing plant for effective condition-based monitoring.

KEYWORDS: *Condition-based, Maintenance, Pumps, Genetic algorithm, Parameter Indicators*

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INTRODUCTION

Condition Based Monitoring is a process of observing the operational status of a system, sub-system, or associated equipment. This is usually carried out to enable a data-based maintenance action to be executed to forestall system or equipment breakdown and its attendant consequence which could lead to loss of life(s), properties, and businesses. It can also be described as the current state assessment of a system and predicting the future state of that system or equipment using certain measurements and calculations. Becker et. al., [1] and Dhillon [2] describe CBM as a systematic process that helps ensure continuous operation of a physical facility to meeting its designed capacity. CBM leads to a maintenance program that focuses preventive maintenance (PM) on specific failure modes likely to occur. Bouyaya et. al.,[3], opined that an organization can benefit from CBM if its breakdowns account for more than 20 to 25% of the total maintenance workload. According to Brauer and Brauer [4], the basic CBM process is composed of seven main steps viz: Identify important items with respect to maintenance, obtain appropriate failure data, develop fault tree analysis data, apply decision logic to critical failure modes, classify maintenance requirements, implement CBM decisions, and apply sustaining-engineering based on field experience. These steps are deployed in CBM technologies which determine item/equipment condition for estimating optimum time for maintenance schedule. Intrusive and

nonintrusive approaches alongside deployment of process parameters is used to assess the overall condition of the equipment. The six major CBM technologies/approaches as discussed by Dhillon and Viswanath [5], [6] are: Vibration monitoring and analysis, Electrical condition monitoring, Thermography, Lubricant and wear particle analysis, Passive (airborne) ultrasonics, and Non-destructive testing. Vibration monitoring considers the magnitude (i.e overall level of vibration) which establishes the severity of vibration and frequency which establishes the content. Vibration monitoring is useful in assessing the condition of rotating equipment and structural stability in a system [7], [8]. The techniques of vibration monitoring and analysis include spectrum analysis, torsional vibration, waveform analysis, shock pulse analysis, and multichannel vibration analysis. The spectrum analysis of vibration signals is commonly used in the fault diagnosis of rotating machines due to its wide range of applications in machines operating at high speed [9], [10]. Therefore, in this study, the vibration monitoring technique was used to evaluate the effectiveness of parameter indices as indicators in CBM of bearings in centrifugal pumps.

Methodology

Centrifugal pumps are among the most common type of pumps used in the oil and gas industry. The centrifugal pump is made up of the casing, impeller, wear rings, shaft, coupling, bearing, sealings, suction and discharge flanges. The bearing plays a critical role in aligning and supporting the shaft for a frictionless rotation [11], [12]. Hence a failure in bearing would lead to the pump failure [13]. In this study, vibration analysis was carried out on the bearing, and data collected which represent the technique used to determine leading, and output indicators are vibration, temperature, speed, current.

A digital vibration analyser was used in the study to monitor the vibration of the bearing. The vibration reading of the electric motor was taken from the drive end of the bearing within thirty-six hours spread over the following conditions of six hours test time: after replacement of a defective bearing, 3 months after replacing the defective bearing, 6 months after replacing the defective bearing, 9 months after replacing the defective bearing, 12 months after replacing the defective bearing and 18 months after replacing the defective bearing respectively. The digital analyser collects data on the frequency of the bearing vibration during the run time. The frequency data is used to generate the corresponding amplitude and frequency spectrum.

Table 1 gives details on the technique, measured data, and object of measurement of the leading and output indicators.

Table 1: Leading and output indicators data collection

S/n	Technique	Measured Data	Measuring Equipment	Description	Point/Object of measurement
1	Vibration	Vibration velocity	Vibration meter	Velocity of bearing	Bearing drive end.
2	Temperature	Differential temperature	Temperature sticker	Chemical indicator calibrated to change colour at a specific temperature.	Bearing, and rolling rack
3	Speed	Angular speed	Stroboscope tachometer	Rotation speed of bearing inner race	Bearing
4	Current	Motor power consumption	Multimeter	Assess the condition of the motor windings.	Electric motor

Data Analysis

Feature extraction calculations for the data collected involved the following:

Fast Fourier Transform (FFT): This is a mathematical algorithm used in the fault diagnosis of rotating machines[14]. FFT takes a vibration time waveform, whether simple or complex, and mathematically calculate the vibration frequencies present along with their amplitudes [15]. Assuming that the waveform of the vibrations setup in the bearing is periodical with Dirichelt condition satisfied, then, the waveform can be expressed as:

$$f_s(t) = \sum_{n=-\infty}^{\infty} f_n e^{\omega t j} \qquad (1)$$

Where: $f_n = \frac{1}{T}\int_0^T f_s(t)e^{-2\pi f t j}dt \;\; and\; T = \frac{1}{f} \;\; is\ the\ period$

Taking $f_s(n)$ as aperiodic function with period T, and the Fourier fundamental angular frequency (Δω) can be defined as:

$$\Delta\omega = 2\pi f;\ \Delta\omega = \frac{2\pi}{T}\ (2)$$

Designating waveform sampling as p, change in angular velocity can be represented as:

$$\Delta\omega = \frac{2\pi}{pT} = \frac{\omega_o}{p}\ (3)$$

When p>1 and where: $\omega_o = 2\pi/T$

The waveform amplitude (A) can be expressed using the Parseval relation as:

$$A = \frac{1}{N}\sum_{n=0}^{N-1} i_s\,[n]^2 = \sum_{k=0}^{N-1} I_s\,[k]^2\ (4)$$

The power at the frequency f_k causing variation in amplitude A is expressed as:

$$P[f_k] = I_s[k]^2 + I_s[N-k]^2 = 2I_s[k]^2\ (5)$$

Where k = 0, 1, 2,…, N = sampled points = 2k

However, the Amplitude of the *m*th harmonic at f_k is assumed to be equal to the square root of the power of the vibrating medium [7].

Hence, from equation (5), we get:

$$A_m[f_k] = \sqrt{P[f_k]} = \sqrt{2I_s}[k]\ (6)$$

Equations 1 to 6 are synchronized in Gwinstek 3.0 sampling window and then exported to MATLAB Simulink windows for generation of the waveform. The algorithm synchronized in Gwinstek 3.0 is used to develop a vibration-based maintenance model which establishes the relationship between the measured signals and the state of the plant.

Genetic Algorithm (GA): The GA repeatedly modifies a population of individual solutions. At each step, an algorithm is generated which selects individual input sample at random from the current population of sample size designated as parents and uses them to produce the children for the next generation. Over successive generations, the population evolves towards an optimal solution.

From the frequency distribution of the vibration signal gotten after replacement of a defective bearing during 6 hours of running, data on the frequency peak and trough range is taken as a random initial population. After which the algorithm creates a sequence of new populations. These populations help converge to an optimal solution that help identify the time of failure of the bearing.

Results on Leading and Output Indicator

Table 2 gives result of the leading and output indicators from the manufacturing plant under consideration.

Table 2: Result on Leading and Output Indicator

Measured Data	Point of Measurement	Start Value	End Value
Vibration Velocity	Bearing	0.5 mm/s	1.046 mm/s
	Electric Motor	0.902 mm/s	0.961 mm/s
Temperature	Bearing	28.3°C	29.0°C
Speed	Bearing inner race	1500 rpm	1500 rpm
Shaft Power	Electric motor	15.5 kW	15.5 kW

Table 2 shows that of all the measured data, the vibration velocity for bearing, Electric motor, and the differential temperature of the bearing recorded significant changes of 109.2%, 6.54% and 2.47% respectively. This implies that the bearing system is susceptible to failure due to vibration. Hence, there is every need to investigate the vibration behaviour at the bearing which gives support to the conveyor system through the FFT technique.

Results on FFT

At six hours: The FFT image of the first six hours of running the bearing after a defective bearing was replaced is shown in Fig. 1. From the figure, it is seen that the running speed of the electric motor is 1500 RPM which is also imparted to the bearing, and this leads to a vibration of 0.5 mm/s of the bearing.

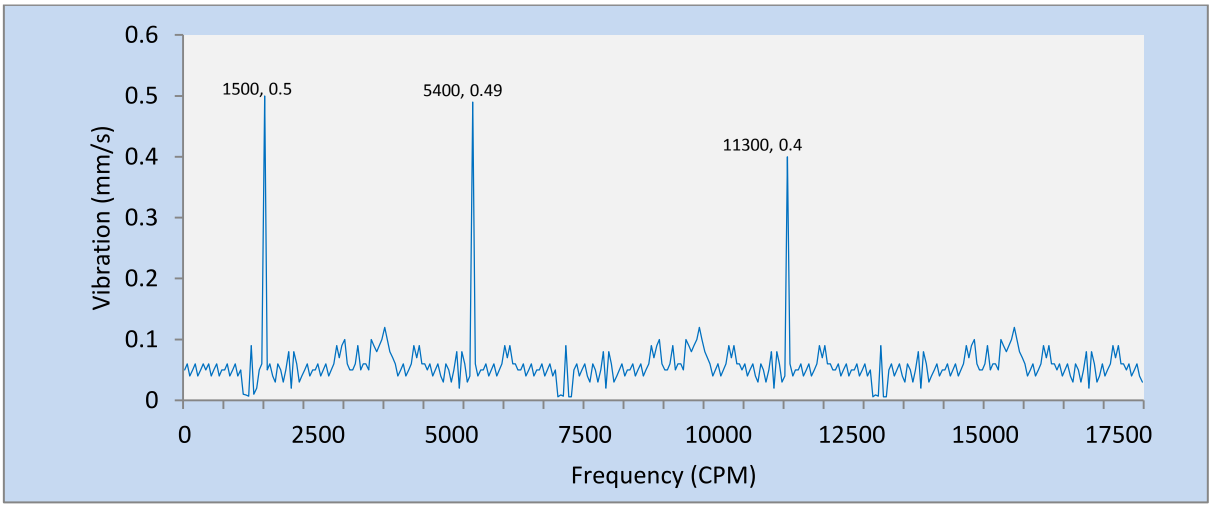

Figure 1: FFT of conveyor system shaft and bearing coupling six hours after installation.

The figure also reveals a first and second harmonics occurring at 3.6X and 7.5X the running speed, occurring at a vibration less than that of running speed. Since the spikes occur at irregular intervals and possess lower vibrations, then the signal doesn't indicate a fault in the conveyor system. This FFT is taken to be the control/baseline spectrum. With this spectrum, deviations occurring at/during other run time condition will be isolated and interpreted accordingly.

At 2160 hours: The graph in figure 2 shows that during the time under observation, there was no significant change/deviation from the trend noticed at 6 hours of operation. The vibration level of the first harmonics increased, while a new spike was noticed at 9X the running speed. This spike could be due to misalignment; however, since its amplitude is less than the fundamental amplitude of vibration, no threat is posed to the smooth operation of the system neither is it an indicator of a benign fault.

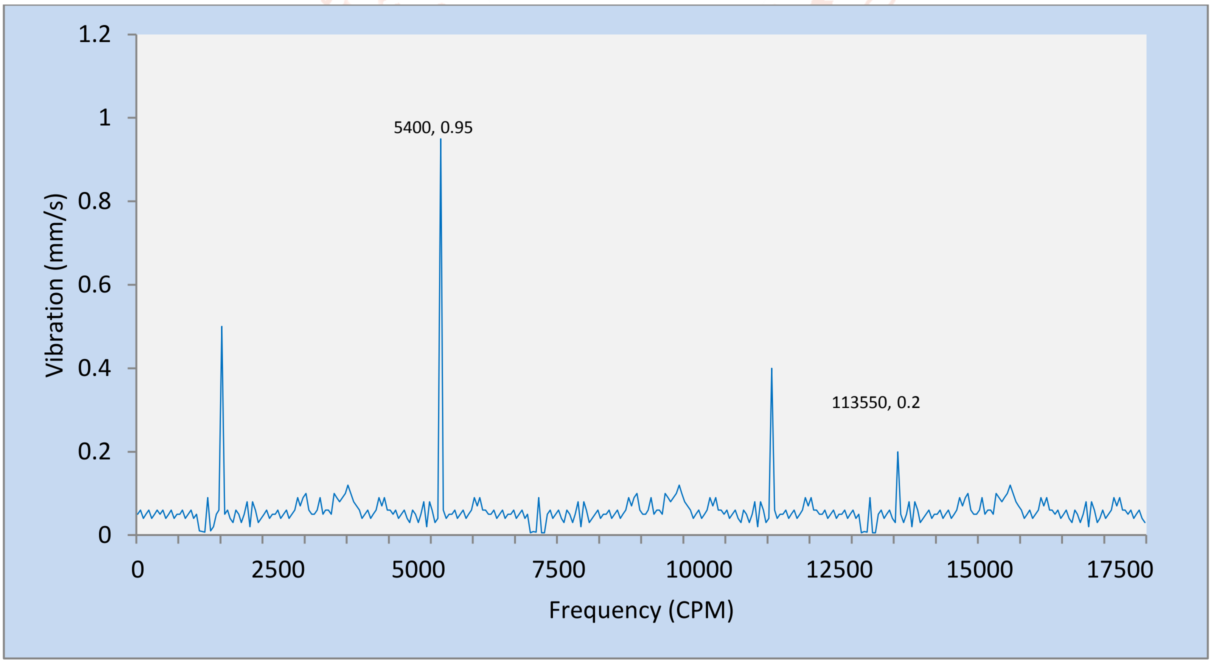

Figure 2: FFT of conveyor system shaft and bearing coupling 2160 hours after installation

At 4320 hours: The spectrum for the runtime of 4320 hours is shown in figure 3. The FFT spectrum showed a significant variation from what was obtained at the runtime of 2160 hours. The FFT spectrum reveals that spikes with decreasing vibration levels were observed at 6.7X, 9.2X, and 11.7X speed of the running speed. These harmonics correspond to frequencies of 166 Hz, 229Hz, and 293Hz respectively.

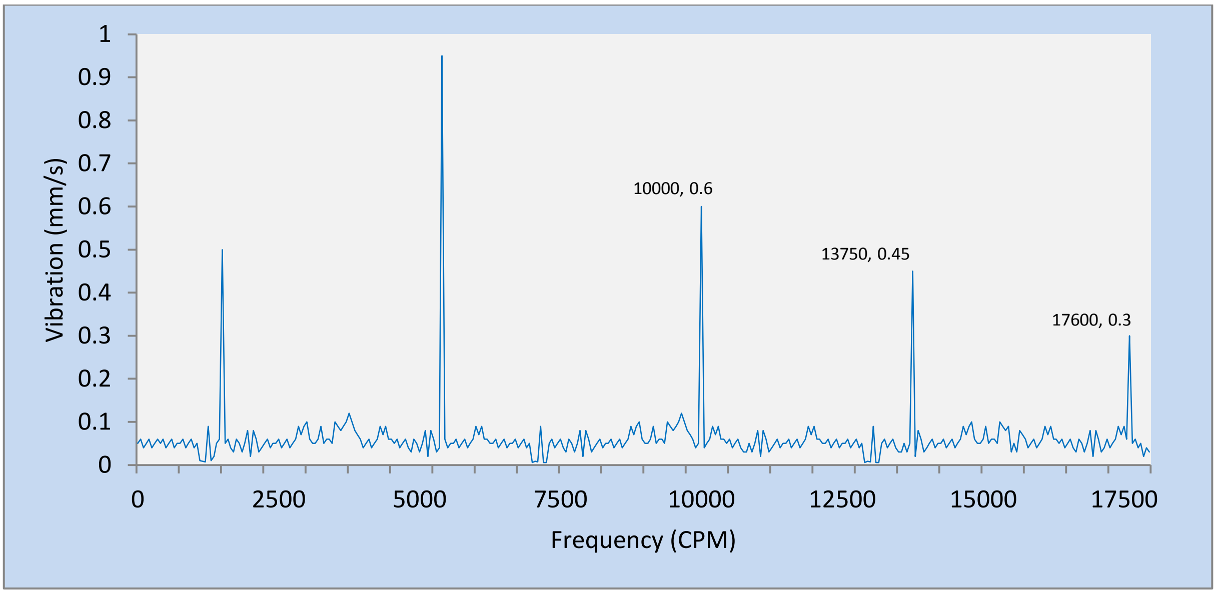

Figure 3: FFT of conveyor system shaft and bearing coupling 4320 hours after installation.

Since this is the first large deviation from the adopted base trend, it is regarded as an early stage in the fault diagnosis/degradation of the bearing. Hence determining/detecting the bearing defect would be done by employing the acceleration enveloping measuring technique. In this method, the bearing defect frequencies can be calculated using equation (6). The equation is keyed into Simulink codes on MATLAB and then overlaid on a vibration spectrum which depicts an enveloped time wave form. Figure 4 shows the enveloped time wave form of the 4320 hours runtime.

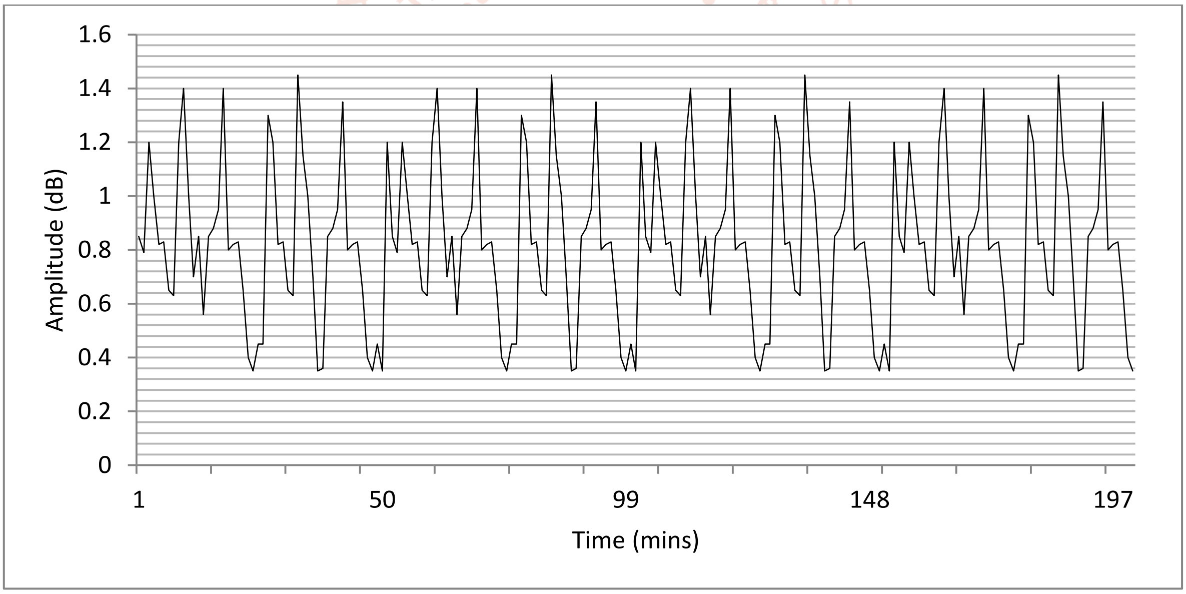

Figure 4: Time waveform of conveyor system shaft and bearing coupling 4320 hours after installation.

From figure 4, we see that the modulation of the signal suggests that defect has been initiated on the bearing inner race. The sudden expansion and contraction of the peaks from high amplitude of 1.45dB to low amplitude of 0.36dB indicates generation of energy as the rolling element rolls over the defect. Hence, the spikes observed in figure 3 are representatives of a burgeoning inner race defect frequencies. At this point, the inner race of the bearing has developed defective points on its surface due to poor lubrication or presence of destructive asperities.

At 6480 hours: Figure 5 shows the FFT spectrum of 6480 runtimes of the bearing system. The harmonics as seen in Figure 5 have abnormally high vibrations and occurring in a random and unorganized sequence. The spikes occur at 1.5X, 2.2X, 5X, and 6.7X the running speed of the electric motor.

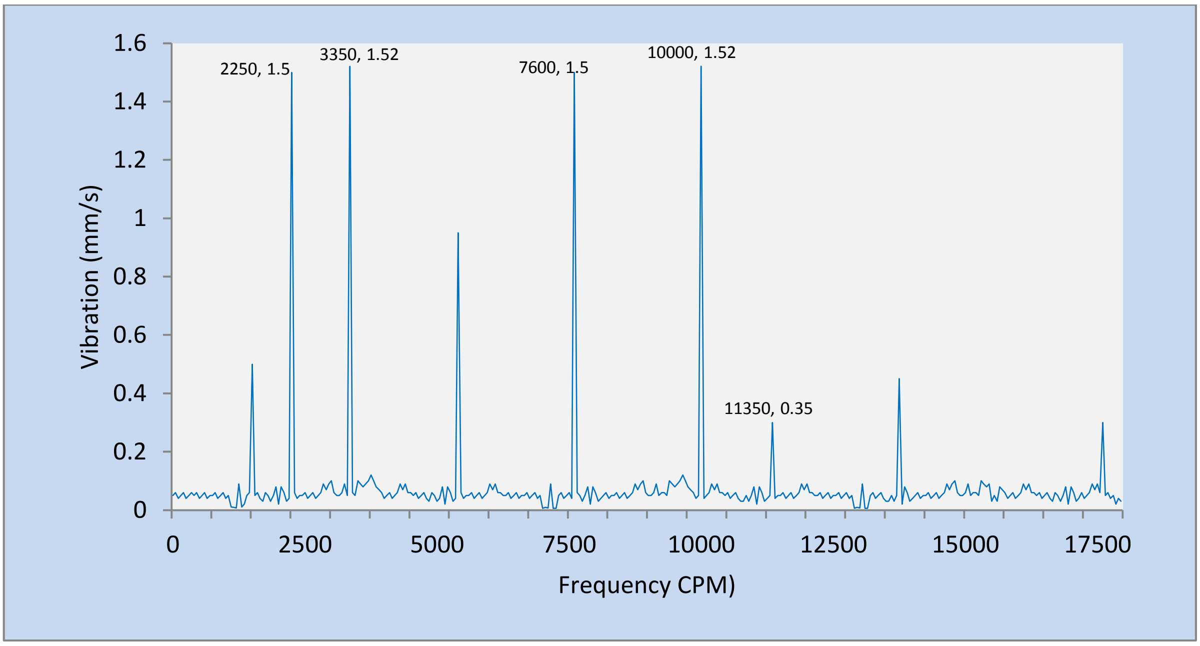

Figure 5: FFT of conveyor system shaft and bearing coupling 6480 hours after installation.

A possible reason for this observation/occurrence is the development of the defect in the inner race of the bearing. Over time, this inner race defect had caused increase in the tolerance fit between the shaft and the surface of the inner race where contact is made. This phenomenon is termed looseness. The figure also shows that the defect on the inner race of the bearing has increased occurring also at 7.6X of the running speed of the electric motor.

At 8640 hours: in running for 8640 hours, the FFT spectrum as seen in Figure 6 shows that harmonics with higher amplitude than the running speed vibrating amplitude was noticed at 2X and 4X the running speed of the electric motor.

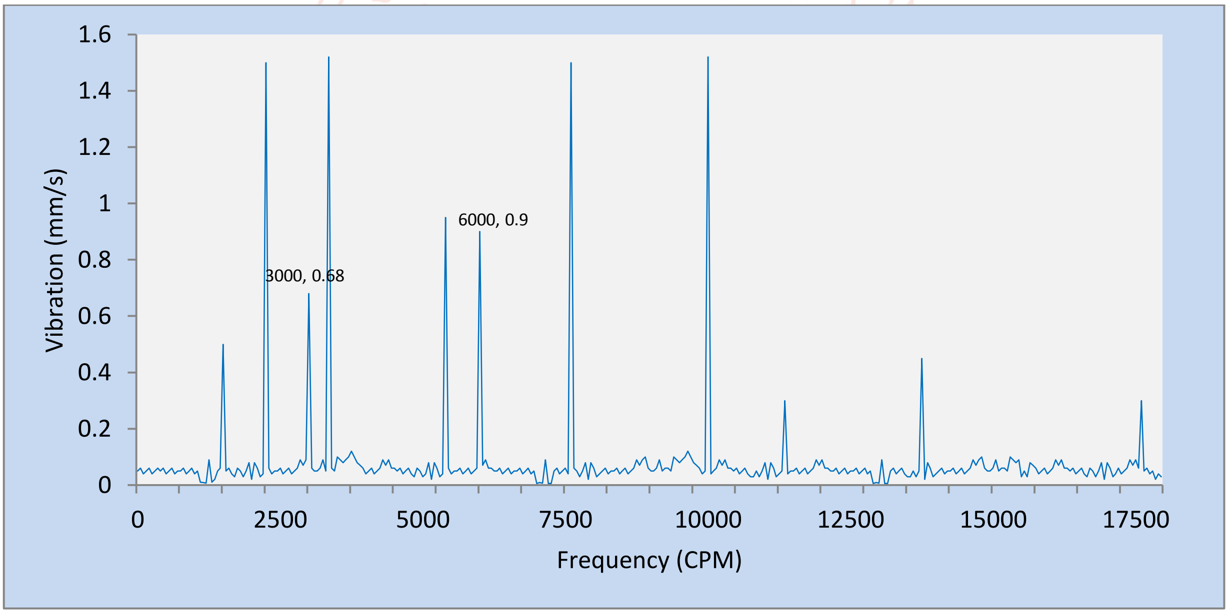

Figure 6: FFT of conveyor system shaft and bearing coupling 8640 hours after installation.

This observation is suspected to be because of misalignment as the centrelines of the bearing and shaft are no longer concentric. This misalignment is a resultant effect of the looseness of the shaft-bearing coupling. This fault causes the bearing to carry a higher load than it should carry according to design specification. This leads to fatigue failure of the bearing in most cases. In Fig. 6, the harmonics at 4X running speed is seen to have vibration amplitude above 50% of the 2X running speed. According to [16], when the vibration amplitude at the second harmonics of the running speed is 50 – 150% of the first harmonics of the running speed, it is possible that coupling damage will occur. Applying this rule to the observation, it is expected that the machine should be scheduled for bearing replacement or risk breakdown.

The plot of vibration against the total running hours of 9480 as seen in figure 7 depicts an exponential curve. This curve is instructive for a proactive approach to maintenance. The ISO 10816-1 [7] Standard for an overall severity of vibration as cited in [16] put forward guideline for categorizing levels of vibration in small medium and large machines.

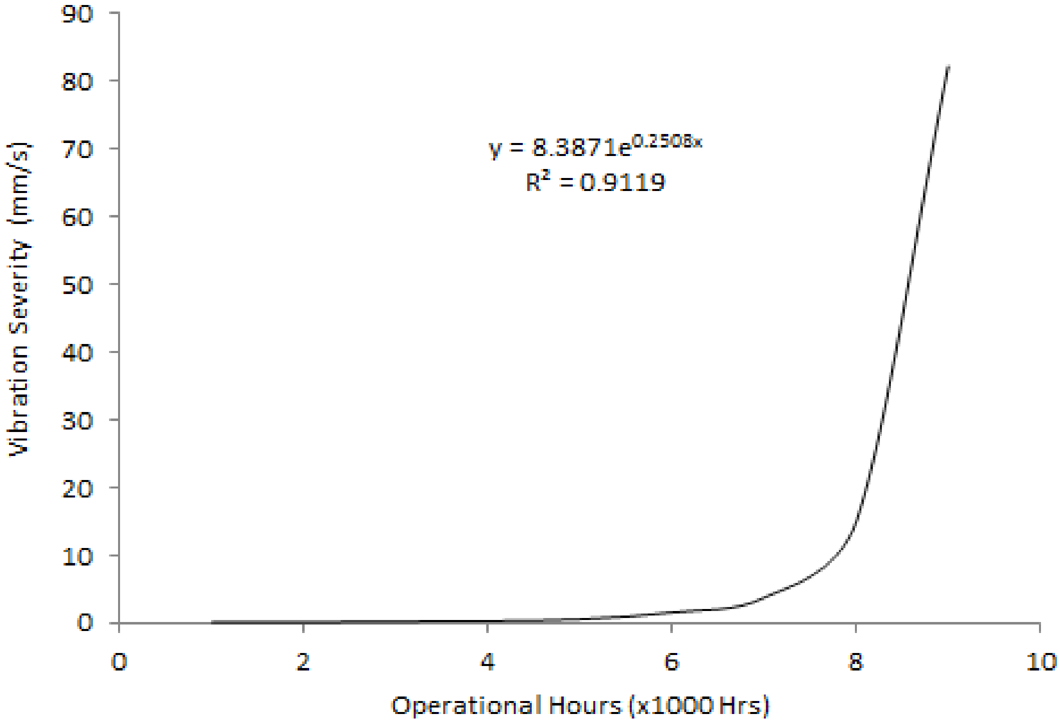

Figure 7: Vibration severity of conveyor system shaft and bearing coupling for a runtime of 9480 hours

The bearing mechanism is categorized as a large machine which falls under the rigid support class III rating according to the ISO Standard 10816 – 1 classification. Also, from Fig 7, it is seen that the model which describes the progression of vibration severity in mm/s with respect to operational hours can be expressed as:

$$\vartheta = 8.3871^{0.2508t} \quad (7)$$

To interpret the curve in Fig. 7 to have a practical implication as regards condition-based monitoring, the vibration severity and velocity range limits for the class III rigid support machines was applied to Fig. 7. The result of this application is seen in Fig. 8

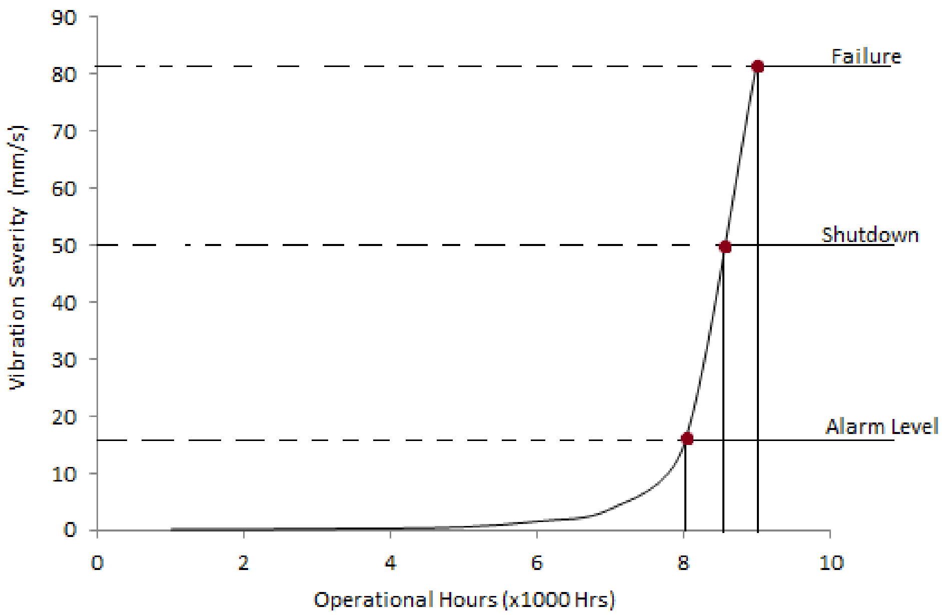

Figure 8: Condition Based Monitoring chart of a conveyor system shaft and bearing coupling for a runtime of 9480 hours.

Alarm level: In figure 8, it is seen that the vibration severity of the bearing system with respect to the interaction between the electric motor shaft and the drive end bearing is within a good range from start of machine operation until it gets to 8000 hours of operation. At this point (also called the alarm point/level), faults such as looseness, unbalance, and misalignment are starting to initiate the speedy degeneration of the bearing. To flatten the curve, it is expedient to review operation procedure with a view to lower the forces (load) acting at the shaft – bearing contact point.

Shutdown: from the alarm point, the faults continue to propagate until the vibration severity becomes 50 mm/s. As seen in Figure 6, at this point, the vibration amplitude at the second harmonics of the running speed is 50 – 150% of the first harmonics of the running speed, leading to coupling damage. It is recommended that a shutdown be initiated at this point to evade a sudden breakdown. This occurs at 8640 hours, and runtimes beyond this point, are at risk of failure of the conveyor system.

Failure: at this point, the system will fail due to subsurface fatigue, and coupling damage if it was properly installed and lubricated. This occurred at 9480 hours of operation.

Results on Genetic Algorithm

From figure 1, the frequency with the highest amplitude is denoted as $A_m[F_k]$, then frequency signals to the left of $A_m[F_k]$ become $A_m[F_{k-1}]$ and frequency signals to the right are denoted $A_m[F_{k+1}]$. Since two types of decision variables (i.e A and F) exist, the following representation of chromosomes was used.

$$\upsilon_k = [(A_{k1}, F_{k1})(A_{k2}, F_{k2})(A_{k3}, F_{k3}) \dots (A_{kn}, F_{kn})] \quad (8)$$

Where k = 1, 2…, Population size.

The initial population size is produced such that each gene is randomly generated in its domain.

Taking the objective function as:

$$F_i[(A_{k1}, F_{k1}) \dots (A_{kn}, F_{kn})] = F_i, (\upsilon_k) \quad (9)$$

where i = 1,2,3… k = population size = 1,2,3…

Hence, standardizing the objective function we get:

$$\widehat{F}_i(\upsilon_k) = \frac{F_i, (\upsilon_k) - \overline{F}_i}{\sigma_i} \quad (10)$$

$where\ i = 1,2,3 \dots\ k = population\ size = 1,2,3, \dots$

$\overline{F}_i$ = mean value of the ith objective function among the frequency of the entire population.

σ_i = standard deviation of the ith objective function

The scaled value of the chromosome size is determined as:

$$C_i(\upsilon_k) = d\widehat{F}_i(\upsilon_k), \quad (11)$$

h = standard deviation of the entire population.

d = scale = 100

The minimum and maximum standardized values of the objective function are gotten as:

$$F_i^{\min(t)} = min\left\{\left(F_i^{(t-1)}, F_i^{(t)}(\upsilon_k) \mid k\, \epsilon\, [1, chr\_size\right)\right\} \quad (12)$$

$$F_i^{\max(t)} = max\left\{\left(F_i^{(t+1)}, F_i^{(t)}(\upsilon_k) \mid k\, \epsilon\, [1, chr\_size\right)\right\} \quad (13)$$

The minimum value represents point at which failure becomes pronounced, while the maximum point represents the point of failure.

For the vibration coefficients the expression in equation 4.7 was used.

$$\lambda_i = \frac{\delta_i}{\Sigma_{i=1}^{n} \delta_i} \quad (14)$$

Where $\delta_i = \frac{F_i^{\max(t)} - F_i^{\min(t)}}{F_i^{\max(t)}}$

The vibrator coefficient is multiplied by the scaled value for each of the generation to give the fitness value for the population. The fitness value which ranged from 0.01 to 1 was derived with the expression:

$$Fit(\upsilon_k) = \Sigma_{i=1}^{n} \lambda_i C_i(\upsilon_k) \quad (15)$$

The operator used in sequencing is the crossover operator. Hence, as opined by [17], [18] the offspring of two chromosomes randomly selected for crossover will yield:

$$O_{k1} = [Cv_{k1} + (1 - C)v_{k2}]$$
$$O_{k2} = [Cv_{k2} + (1 - C)v_{k1}]$$

The chromosomes generated were used to develop the GA m-files in MATLAB software. The GA iterates around the generational loop until gen = MAXGEN and then terminates. The result of the GA is shown below:

[Y, I] = max(ObjV)
Y = 13.43
I = 87

"Y" represents the subgroups of the whole population. Theses subgroups are as earlier mentioned are the months of operation, while "I" represents the amplitude of the vibration. This result implies that failure will set in (approximately) after 9674 hours of operation with a vibration severity of 87mm/s. Fig. 9 shows a plot of the solution obtained by GA analysis.

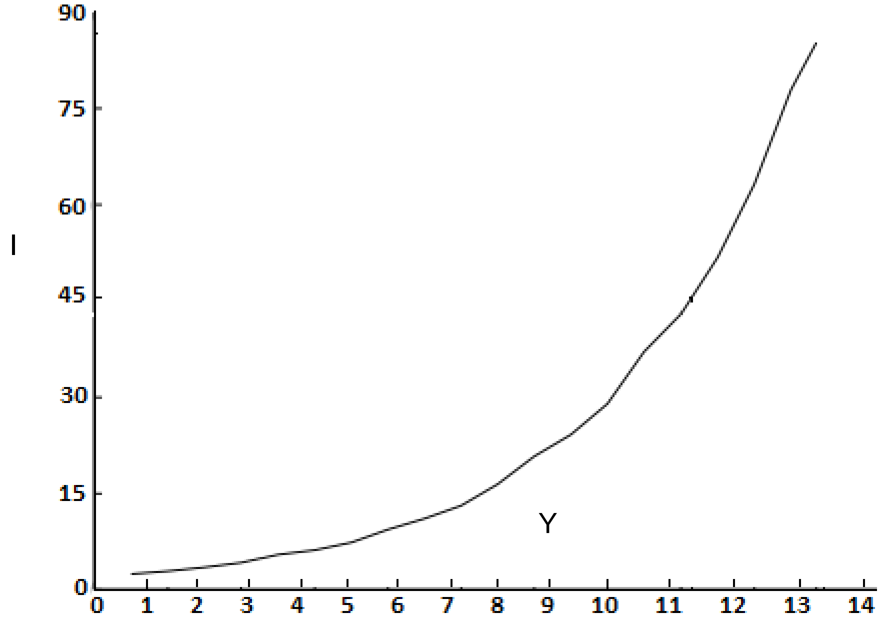

Figure 9a: Solution obtained from GA

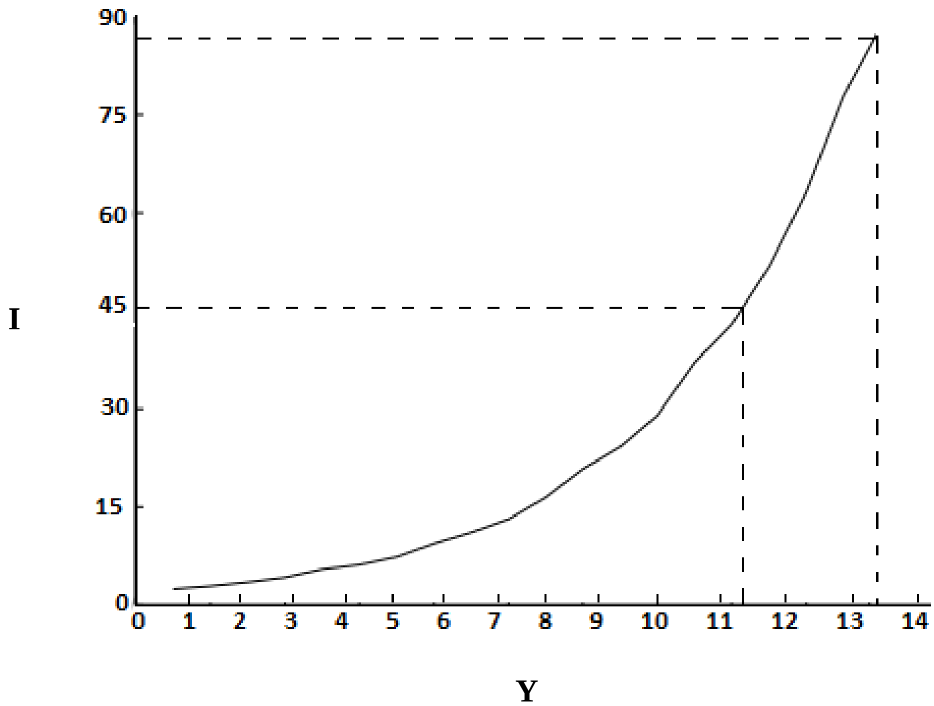

Figure 9b: Solution obtained from GA showing shutdown and failure points.

Figure 9 shows that the solution to the CBM problem takes an exponential trend, corresponding with FFT result. In Fig. 9b, it is observed that after the point 11.3 (which corresponds to 8121 hours) in the subgroup axis, little increases along the axis translate to large changes on the amplitude axis. This suggests that at this point, the vibration amplitude at the second harmonics of the running speed is 50 – 150% of the first harmonics of the running speed. Hence, it is denoted the Shutdown point (11.3, 45), while the point (13.44, 87) is denoted the failure point.

Validation of FFT result

A comparison of the results obtained by the FFT and GA methods is shown in table 3 below.

Table 3: FFT and GA results

	FFT		GA	
	Operation Hours	Vibration Severity	Operation Hours	Vibration Severity
Shutdown Point	8640	50mm/s	8121	45mm/s
Failure Point	9480	82mm/s	9674	87mm/s

Conclusion

The study conducted focused on using parameter indices as indicators in Condition Based Monitoring of equipment. To achieve this, the study established leading/output indicators which interface with the maintenance schedule and procedure. These indicators establish the current state of the plant and identify what parameters/activity is responsible for a noted trend. Vibration analysis was used to establish the relationship between the plant equipment maintenance procedure and the state of the plant. This was achieved by using FFT technique and validated using GA method. The model developed is helpful in scheduling maintenance operations to avoid unnecessary halt in the production line due to failure of a component. The study concludes that the use of parameter indicators is a necessary guide in positioning a process/production line/manufacturing plant for effective condition-based monitoring.

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